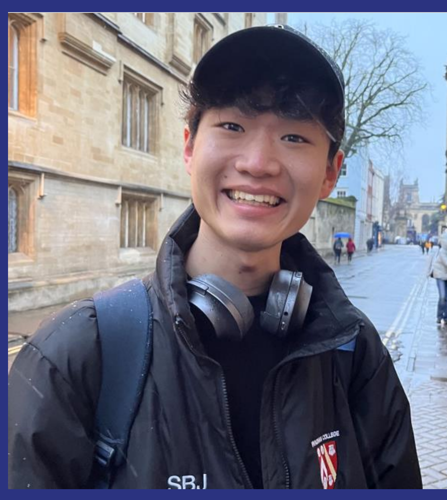
Advanced Acoustic Emission Techniques with Cylindrical Lithium-Ion Cells

Non-invasive in-situ monitoring of battery safety and performance



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ABSTRACT

Understanding the safety characteristics of the widely deployed cylindrical Li-ion batteries (LIBs) is crucial as they can result in significant chemical and fire hazards when failure occurs [1].

Acoustic emission (AE) is a cost-effective, non-invasive rapid diagnostic technique whereby battery degradation phenomena including electrode expansion, crack formation and gas production can be detected using a piezoelectric sensor. This can be used to determine state of health (SoH) and track key safety metrics. This project combines AE techniques with machine learning (ML) and X-Ray CT analysis to assess the SoH of such LIBs.

MOTIVATION

Despite the ubiquity of cylindrical cells, AE techniques with cylindrical cells currently lack detailed research and are challenging because:

- AE waves reflect, transmit and interfere with one another in complex ways when propagating through 15–25 layers of curved electrodes [2].
- The common '*jelly-roll*' structure leads to internal scattering and Lamb waves travelling in longitudinal & circumferential directions [3,4].

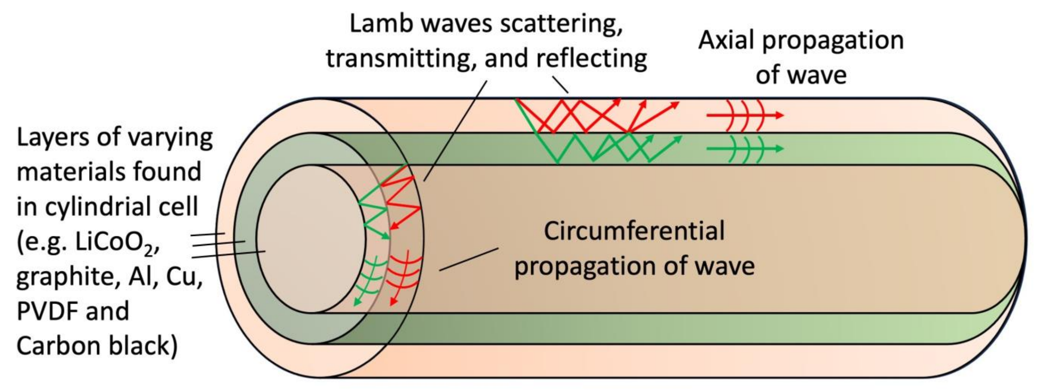

Figure 1. Simplified visualisation of lamb wave propagating axially and circumeferntially in a cylindrical cell.

METHODOLOGY

- A pristine P42A cylindrical cell was secured in a bespoke holder shown in Figure 2 with couplant applied on necessary interfaces. 3 sensor positions along the slider were marked: 18, 36, 54mm (relative to the negative tab). For each position, the cell was cycled at C/3 for 10 cycles between 2.5 and 4.2V. The same was done at 1C. Following this, an aged P42A (80% SoH) was examined using a similar protocol.

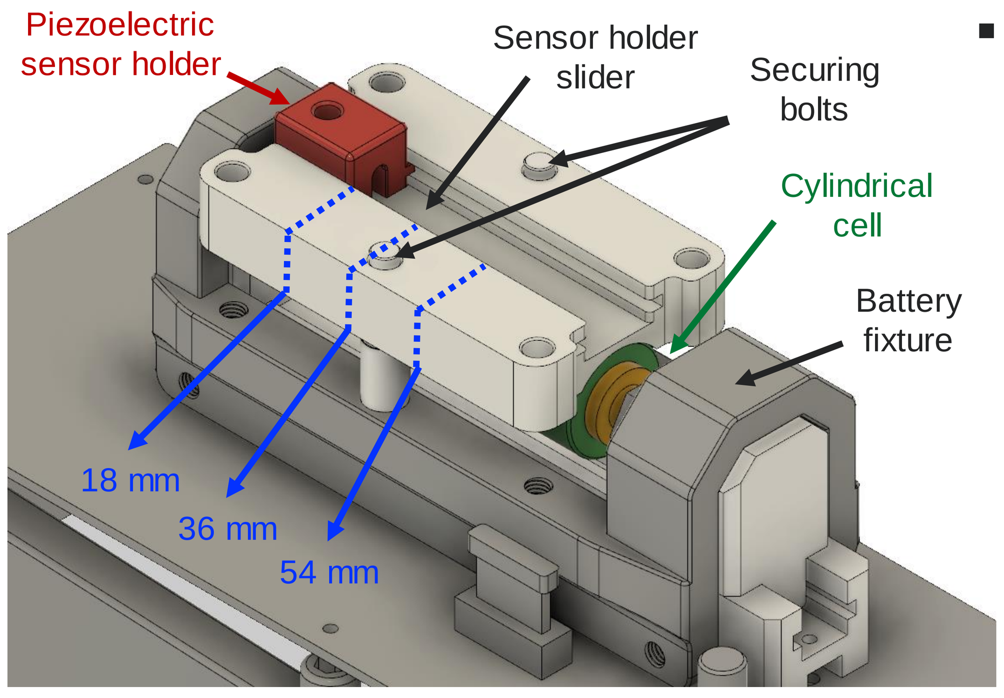

Figure 2. AE signal acquisition hardware setup.

- AE signals over the threshold of 29dB (called '*hits*') were recorded using AEwin software. Individual hits were visualised using Python code developed during the placement which organises waveforms and plots the unfiltered signal, band-pass filtered signal and FFT.

CYCLING DATA AND AE HITS ANALYSIS

- Large jumps (> 20 aJ) in cumulative absolute energy (CAE) were observed in pristine cells cycling at 1C & C/3 as shown in Figure 3(d-f), but not in aged cells cycling at 1C & C/3.
- In various pristine & aged cell cycling runs, there were regular AE hits of similar amplitudes at the 2.5V point of the voltage cycle, where discharge to charge transition occurs; these regular waveforms shared a distinct sustained pulse shape shown in Figure 3(g).
- Full data showed no clear/consistent patterns of AE hits when comparing between runs at different transducer positions and different C-rates, as partially shown in Figure 3(a-c).

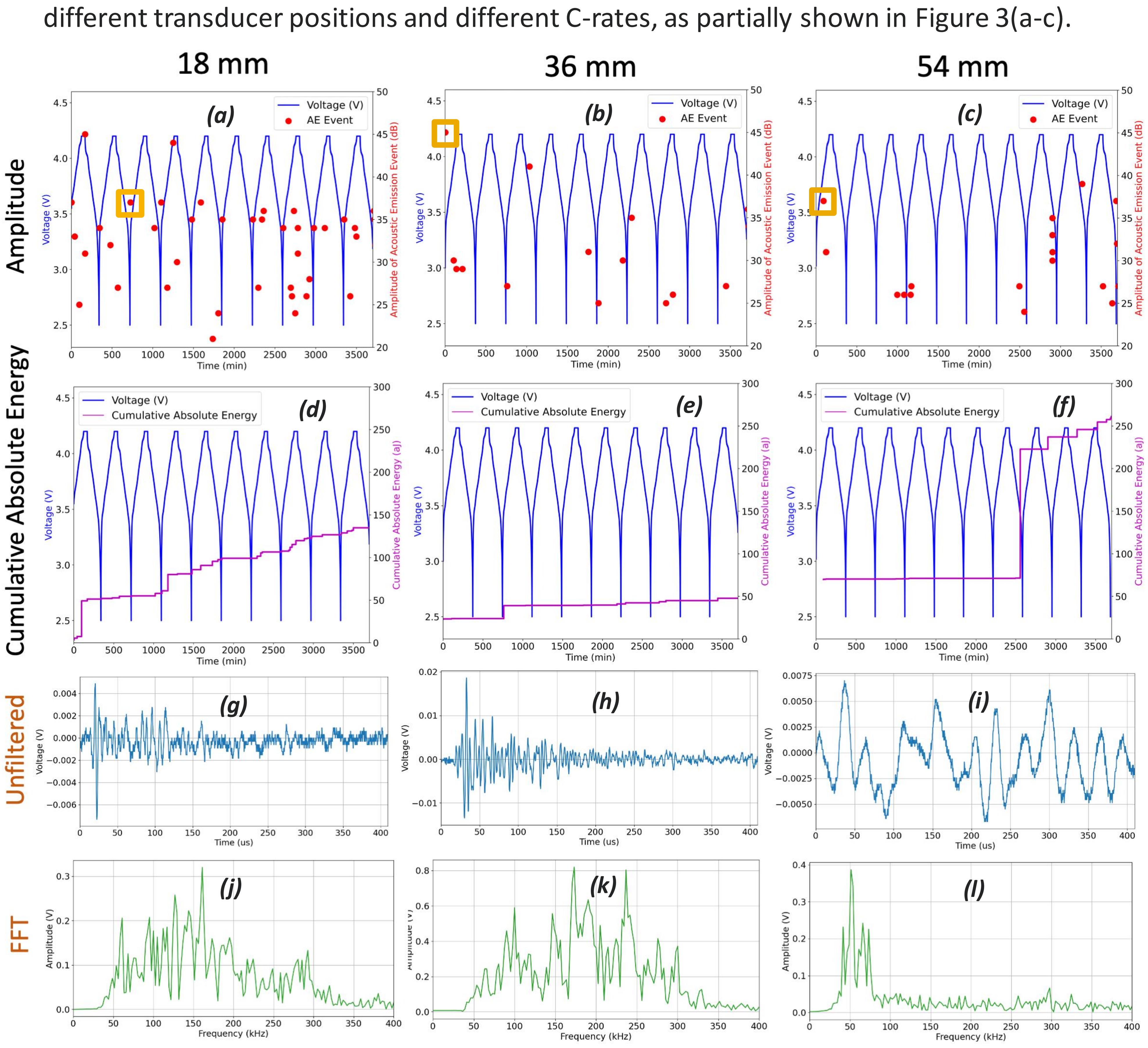

Figure 3. C/3 pristine cell cycling data (columns indicate transducer position). Row 1: Plots of voltage & hits amplitude. Row 2: Plots of voltage & CAE. Row 3 & 4: Unfiltered waveform & FFT of encircled example hit (orange).

MACHINE LEARNING MODEL

- Principal component analysis (PCA) and autoencoder deep neural networks (DNN) were used to reduce 14-dimensional acoustic features of pristine cell waveforms to a visualisable 3-dimensional dataset.
- Unsupervised k-means clustering was used to group waveforms according to acoustic properties, where k was optimised using graphical & silhouette score analysis (k=4).
- Clustering results (and full ML code):

	Cluster 0	Cluster 1	Cluster 2	Cluster 3
PCA + k-means cluster	High amplitude (0.006 - 0.02 V) pulse-type signal, e.g. Figure 3(h)(k)	Noise & low amplitude (0.001-0.004 V) pulse-type	Noise & low amplitude (0.001-0.004 V) pulse-type	Continuous type signal, e.g. Figure 3(i)(l)
Auto encoder + k-means cluster	High amplitude (0.006 - 0.02 V) pulse-type signal, e.g. Figure 3(h)(k)	Noise, high & low amplitude pulse-type	Continuous type signal, e.g. Figure 3(i)(l)	Noise & low amplitude (0.001-0.004 V) pulse-type

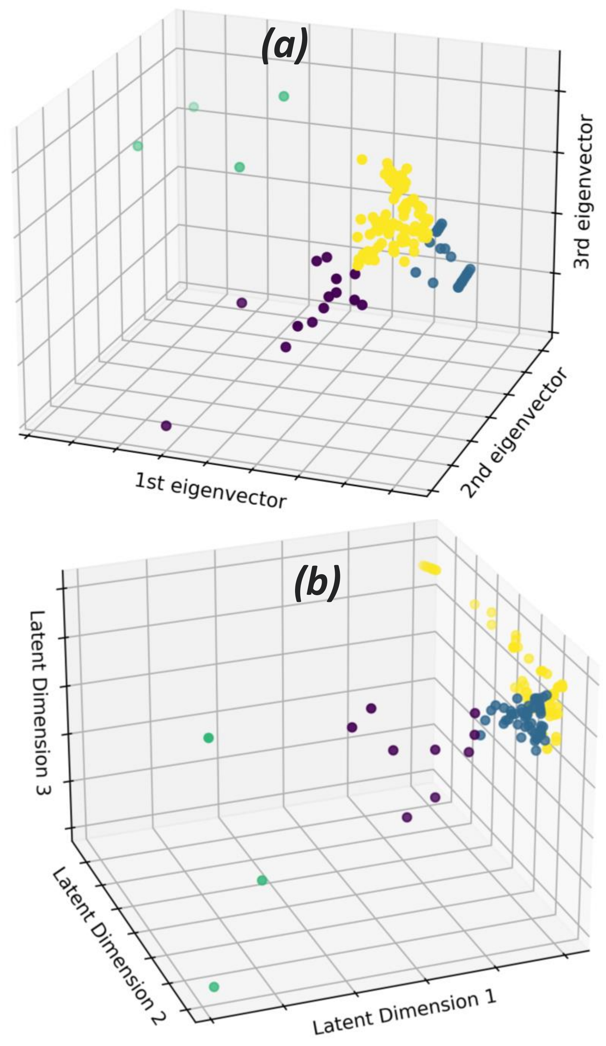

Figure 4. Pristine cell waveforms 14-dimensional features clustered and mapped onto 3 dimensions using (a) PCA (b) autoencoders.

- Supervised ML was also employed by training a DNN to classify aged and pristine waveforms, as shown in Figure 5.
- Classifier accuracy on unseen test data was 93.8%, shown in Figure 6

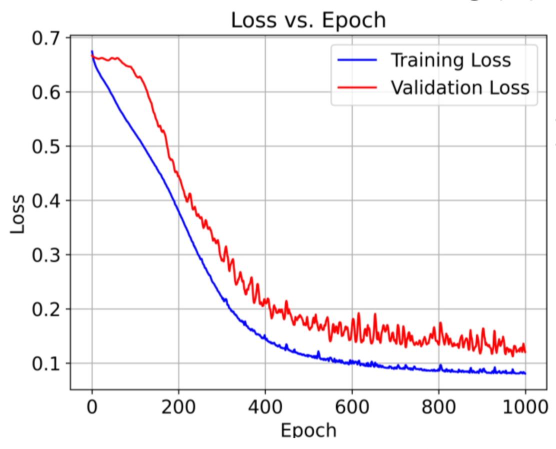

Figure 5. Training of DNN.

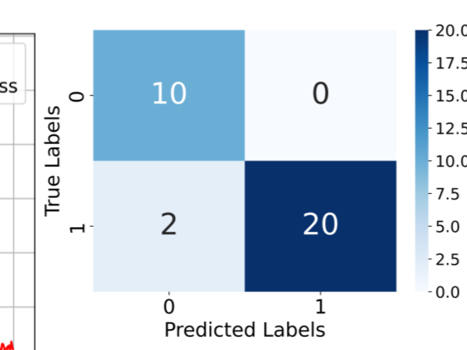

Figure 6. Confusion matrix of classifier, where aged = 0 and pristine = 1.

X-RAY CT ANALYSIS

CT scans show electrode deformation, suggesting aged-pristine classifier may be detecting changes in acoustic behavior due to structural changes.

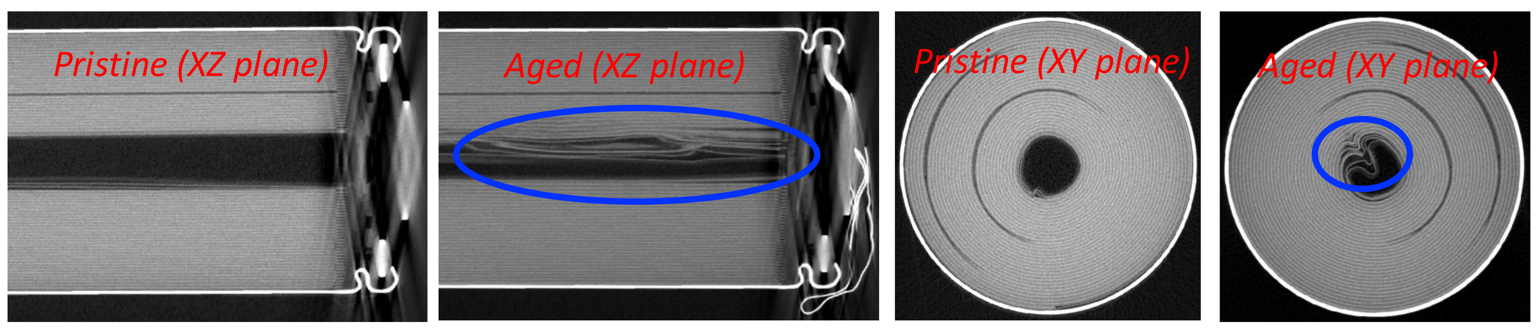

Figure 6. Nikon XTH 225 X-ray CT scans of pristine & aged cells. Deformation in blue.

CONCLUSION

- By analysing frequency of large CAE jumps over many cycles and using developed supervised ML classifier, we can make successful binary predictions on SoH of cylindrical cells (aged vs. pristine)
- Dataset accounts for different transducer positions → Classifier is less sensitive to experimental biases (e.g. surface conditions) → In fact, CT suggests classifier may be sensitive to structure-induced acoustic changes.
- Waveforms clustered using unsupervised ML correspond to existing research[5] who also detected pulse-type signals (associated with electrode cracking) and continuous signals (associated with gas formation & electrode expansion) [5] → Unsupervised ML technique could be an insightful in-situ diagnostic technique for identifying degradations occurring in cylindrical cells and their internal causes.
- **Impact:** Significant step towards cost-effective diagnostics for EVs & electrical systems with cylindrical cells
- **Next steps:** Analyse cells at incrementally varied SoH, increase dataset size to improve ML, aim to publish

REFERENCES

[1] National Transportation Safety Board. (2020). *Safety Risks to Emergency Responders from Lithium-Ion Battery Fires in Electric Vehicles*.

[2] Hsieh, A. G., Bhadra, S., Hertzberg, B. J., Gjeltema, P. J., Goy, A., Fleischer, J. W., & Steingart, D. A. (2015). Electrochemical-acoustic time of flight: In operando correlation of physical dynamics with battery charge and health. Energy and Environmental Science, 8(5), 1569–1577. https://doi.org/10.1039/c5ee00111k

[3] Majasan, J. O., Robinson, J. B., Owen, R. E., Maier, M., Radhakrishnan, A. N. P., Pham, M., Tranter, T. G., Zhang, Y., Shearing, P. R., & Brett, D. J. L. (2021). Recent advances in acoustic diagnostics for electrochemical power systems. In *JPhys Energy* (Vol. 3, Issue 3). IOP Publishing Ltd. https://doi.org/10.1088/2515-7655/abfb4a

[4] Chahbaz, Mustafa, & Hay. (1997). Inspection of Cylinders Using Ultrasonic Guided Waves. NDTnet, 2(5).

[5] Zhang, K., Yin, J., & He, Y. (2021). Acoustic emission detection and analysis method for health status of lithium ion batteries. *Sensors (Switzerland)*, *21*(3), 1–17. https://doi.org/10.3390/s21030712

BIOGRAPHY

Seung-Bin (Jake) Joo is studying MEng Engineering Science at the University of Oxford. He is interested in robotics, autonomous technology and mechatronics. He may potentially pursue a PhD and aspires to contribute to pushing engineering frontiers in ways that help others.

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